6. Transformation and Enhancement of Climate Change Policy Indicators

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6.1. Introduction

To understand the effects of climate change policies not only on the environment but also on business and the economy, substantial effort has been devoted to creating climate policy indicators. Such indicators can be useful for addressing a major research question, namely: how do climate policies impact the economy and the environment? Likewise, in recent years there has been increasing interest in identifying reliable climate policy and governance indicators because of the explosion in green growth policies, especially in response to Covid-19.[3] Indeed, the amount of money earmarked for green growth is a major share. Policymakers thus need to know that this money is well spent and convey to their constituents the level of effectiveness. Similarly, investors and companies, in particular,

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3. Caroline Kuzemko, et al., 'Covid-19 and the politics of sustainable energy transitions,' *Energy Research & Social Science* 68 (October 2020): 101685. https://doi.org/10.1016/j.erss.2020.101685 sustainably-minded investors and highly polluting companies have a big stake in how these emerging climate and green growth policies impact their businesses. Consequently, metrics for climate change governance are now more important than ever before.

Yet, we still do not have a good grasp on how firms and economies react to such policies.[4] Climate policy indicators should ideally be easy to calculate, produced annually, cardinal, and available to a large array of different pollutants.[5] Furthermore, these indicators ought not to only address certain sectors or industries but rather extend to broader parts of the economy and across countries.[6] More peripheral issues are the sensitivity to data revisions, variability in the data, and small sample issues.[7] These complexities and the numerous array of climate policies in place worldwide make indicators construction and transformation an arduous but important task.

To ameliorate the underlying issues of climate policy governance metrics and indicators, we suggest that machine learning (ML), pattern discovery, and deep learning (DL) techniques should be deployed. Whilst these methods are already well-developed in other fields of scholarship,[8] they have only just begun to be used within the climate change policy and governance space. This is the main crux of this chapter.

This chapter posits that transformative metrics are becoming increasingly relevant and important for climate and environmental governance, which is

4. Daniel J. Henderson and Daniel L. Millimet, 'Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States: A Nonparametric Reassessment,' *The Review of Economics and Statistics* 89, no. 1 (February 2007): 178–83. https://doi.org/10.1162/rest.89.1.178; Claire Brunel and Arik Levinson, 'Measuring the stringency of environmental regulations,' *Review of Environmental Economics and Policy* 10, no. 1 (Winter 2016): 47–67. https://doi.org/10.1093/reep/rev019; Nicole M. Schmidt and Andreas Fleig, 'Global patterns of national climate policies: Analyzing 171 country portfolios on climate policy integration,' *Environmental Science & Policy* 84 (June 2018): 177–85. https://doi.org/10.1016/j.envsci.2018.03.003; David Popp, *Environmental policy and innovation: a decade of research* (Cambridge: National Bureau of Economic Research, 2019); Marzio Galeotti, et al., 'Environmental policy performance and its determinants: Application of a three-level random intercept model,' *Energy Policy* 114 (March 2018): 134–44. https://doi.org/10.1016/j.enpol.2017.11.053

5. Brunel and Levinson, 'Measuring the stringency.'

6. Ibid.; Galeotti, et al., 'Environmental policy performance.'

7. Michela Nardo, et al., *Tools for Composite Indicators Building*. (Ispra: Joint Research Centre European Commission, 2005).

8. Anil K. Jain, 'Data clustering: 50 years beyond K-means,' *Pattern Recognition Letters* 31, no. 8 (June 2010): 651–66. https://doi.org/10.1016/j.patrec.2009.09.011; Wright, et al., 'Sparse representation.'

aligned with the theme of this book. In this line, we explore how ML, pattern discovery, and DL can be used to enhance our understanding of the environmental and economic impacts of climate policies around the world. Building upon previous literature that explores some climate policy indicators,[9] we identify the main concerns researchers need to take into account when constructing indicators. Similarly, we discuss several previous transformations of climate policy indicators. In addition, we present a sample index using our transformation of existing indices, which demonstrates how our methods can work in practise. Finally, we suggest several directions for future research.

6.2. Background

Climate policies have become widespread throughout the world, addressing a number of complex environmental, economic, and social issues. Researchers have identified hundreds of environmental policy indicators such as the OECD's 'environmental policy stringency index' and Yale's 'environmental performance index,' many of which are specifically focused on climate policy.[10] Testament to the incredible diversity and dispersion of climate policies, researchers at the Grantham Research Institute on Climate Change have identified 2,122 climate laws across nearly every country in the world. Covering so much ground, climate policies are also quite heterogeneous.[11] There is no 'one size fits all' climate change policy. Consequently, measuring the economic and environmental impacts of climate policy has become exceedingly difficult.

Fortunately, governments, grantors, universities, and companies have already recognised the importance of having reliable climate policy indicators. This led to several relatively trustworthy indicators variously deployed to test

9. Rajesh Kumar Singh, et al., 'An overview of sustainability assessment methodologies,' *Ecological Indicators* 15, no. 1 (April 2012): 281–99. https://doi.org/10.1016/j.ecolind.2011.01.007

10. Singh, et al., 'An overview of sustainability;' Rajesh Kumar Singh, et al., 'An overview of sustainability assessment methodologies,' *Ecological Indicators* 9, no. 2 (March 2009): 189–212. https://doi.org/10.1016/j.ecolind.2008.05.011; Christoph Böhringer and Patrick E.P. Jochem, 'Measuring the immeasurable—A survey of sustainability indices,' *Ecological Economics* 63, no. 1 (June 2007): 1–8. https://doi.org/10.1016/j.ecolecon.2007.03.008

11. Singh, Rajesh Kumar, et al., 'Sustainability assessment methodologies.'

empirical research, give policy-makers an idea of how climate policy impacts the environment, and as a tool for investors and companies.[12] Some attempts have been made to transform 'off-the-shelf' climate policy indicators,[13] which we define as indicators that are already developed by governments, research institutes, and academics. Nevertheless, while the transformation of indicators can enhance the reliability and consistency of indicators, several aspects need to be considered before such transformation can be realised. In this section, we define some underlying issues that can occur during climate policy indicators transformation. We then introduce several climate policy indicators widely in use already. Lastly, we discuss previous transformations of climate policy and introduce our example to demonstrate how to expand upon these methods in future research.

The Demand for Climate Policy

How to achieve green growth through climate policies is becoming an increasingly pressing question for policymakers;[14] for instance, a renewed call for green recovery arose in 2020 in response to COVID-19.[15] Because green growth implies the fact that 'technological change and substitution will improve the ecological efficiency of the economy, and that governments can speed this process with the right regulations and incentives,'[16] green growth can be realised through climate policy, innovation, and industrial upgrading. This has led to a rising demand to understand the impacts of climate policies on the economy.

In this framework, a number of empirical models have been developed to understand how these policies impact innovation, growth, economy, and the

12. Stefan Ambec, 'Gaining competitive advantage with green policy,' in *Green Industrial Policy: Concept, Policies, Country Experiences*, eds. Tilman Altenburg and Claudia Assmann. (Geneva: UN Environment and German Development Institute, 2017), 38–50; Mark A. Cohen and Adeline Tubb, 'The Impact of Environmental Regulation on Firm and Country Competitiveness: A Meta-analysis of the Porter Hypothesis,' *Journal of the Association of Environmental and Resource Economists* 5, no. 2 (April 2018): 371–99. https://doi.org/10.1086/695613

13. Galeotti, et al., 'Environmental policy performance.'

14. Jonas Meckling and B. Allan Bentley, 'The evolution of ideas in global climate policy,' *Nature Climate Change* 10, no. 5 (May 2020): 434–38. https://doi.org/10.1038/s41558-020-0739-7

15. Kuzemko, et al., 'Covid-19 and the politics.'

16. Jason Hickel and Giorgos Kallis, 'Is Green Growth Possible?' New Political Economy 25, no. 4 (April 2019): 470. https://doi.org/10.1080/13563467.2019.1598964 environment.[17] Frequently, researchers seek to understand how climate policy induces innovation, development, deployment, and installation of renewable energy technologies that do not emit harmful greenhouse gases (GHGs) and which are thus a main component for meeting climate goals.[18] In general, empirical analyses involve designating the climate policy indicator as the main explanatory variable of interest.[19]

Climate Policy Measurement Issues

Despite the demand for reliable indicators, many remain problematic.[20] Indeed, in an influential article, Brunel and Levinson highlight some underpinning issues associated with the development of environmental and climate policy indicators.[21] They contend that, in the absence of more concerted efforts to address the complexities inherent to climate policy indicators, spurious and often contradictory empirical results will be common. In this vein, climate policy indicators are highly susceptible to human biases, which is the main motivation for writing this chapter.

Transformation and application of existing indicators while less susceptible, also face a number of difficulties. For these reasons, we suggest and demonstrate how ML, pattern discovery, and DL could be applied in these contexts. Whilst ML, pattern recognition, and DL are already widely used in related research,[22]

17. Stefan Ambec, et al., 'The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness?' *Review of Environmental Economics And Policy* 7, no. 1 (Winter 2013): 2–22. https://doi.org/10.1093/reep/res016

18. Nick Johnstone, Ivan Haščič, and Margarita Kalamova, *Environmental Policy Design Characteristics and Technological Innovation: Evidence from Patent Data (Working Paper)* (Paris: OECD Publications, 2010). https://dx.doi.org/10.1787/5kmjstwtqwhd-en; Yana Rubashkina, Marzio Galeotti, and Elena Verdolini, 'Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors,' *Energy Policy* 83 (August 2015): 288–300. https://doi.org/10.1016/j.enpol.2015.02.014; Yun Wang, Xiaohua Sun, and Xu Guo, 'Environmental regulation and green productivity growth: Empirical evidence on the Porter Hypothesis from OECD industrial sectors,' Energy Policy 132 (2019): 611–19. https://doi.org/10.1016/j.enpol.2019.06.016

19. Ambec, et al., 'The Porter Hypothesis at 20.'

20. Cohen and Tubb, 'Impact of Environmental Regulation.'

21. Brunel and Levinson, 'Measuring the stringency.'

22. Jain, 'Data clustering;' John Wright, et al., 'Sparse representation for computer vision and pattern recognition,' *Proceedings of the IEEE* 98, no. 6 (June 2010): 1031–44. https://doi.org/10.1109/JPROC.2010.2044470 they are not extensively applied to climate policy yet. These methods can help identify, classify, and cluster climate policies based on public sentiment (e.g., on Twitter streams), aggregate and fine-tune satellite imagery (e.g., Carbon Space Inc.), which has been done for the UN Sustainable Development Goals (SDGs),[23] or automate the progress on emissions reductions of GHGs covered by the Kyoto Protocol.[24] Another recent technique is to automatically digest data submitted as Nationally Determined Contributions (NDCs) under the Paris Agreement, which was suggested recently by Franke et al.[25] These tools and methods are discussed later in this chapter. Immediately below we explain important considerations researchers should take during the construction of climate change policy indicators.

Brunel and Levinson identify four measurement issues that lead to underlying issues in climate policy indicators that occur during construction, transformation, and afterward application. These issue areas are (1) multidimensionality, (2) simultaneity, (3) industrial composition, and (4) capital vintage.[26] We briefly review their important arguments below. Subsequently, we explain different types and typologies of climate policies that are intrinsically important in the transformation and application of indicators.

Multidimensionality

Multidimensionality refers to the issue of space and geography. The geographical application of climate is paramount, especially because GHGs can freely travel across country borders after they are emitted. Indeed, this 'collective action' problem has bogged down multilateral climate change negotiations for

23. Nataliia, Kussul, et al., 'A workflow for Sustainable Development Goals indicators assessment based on high-resolution satellite data,' *International Journal of Digital Earth* (May 2019): 309–21. https://doi.org/10.1080/17538947.2019.1610807

24. Yongming Xu, et al., 'Evaluation of machine learning techniques with multiple remote sensing datasets in estimating monthly concentrations of ground-level PM2.5,' *Environmental Pollution* 242, part B (November 2018): 1417–26. https://doi.org/10.1016/j.envpol.2018.08.029

25. Laura Franke, Marco Schletz, and Søren Salomo. 'Designing a blockchain model for the Paris agreement's carbon market mechanism,' *Sustainability* 12, no. 3 (February 2020): 1068. https://doi.org/10.3390/su12031068

26. Brunel and Levinson, 'Measuring the stringency.'

decades.[27] Therefore, researchers must take into account location-specific aspects of climate policy (e.g., its intended geographical scope and target) during both the construction and application of climate policy indicators.

Simultaneity

Without due consideration of temporal differences (e.g., the length of time a policy has been in place, the stipulated target year for emissions reductions, and the intended longevity of a policy), the issue of simultaneity can result in a number of measurements and empirical modelling problems.[28] Concerted efforts are, thereby, required so that policymakers can compare policies over time and across jurisdictions. Indeed, the NDCs under the Paris Climate Agreement are intrinsically reliant compared to GHGs reduction targets at specified baseline (past) and future target dates.[29]

Capital Vintage and Industrial Composition

Climate policies can have widely varied impacts on technology and industrial trajectories. The stipulation that industrial equipment must emit fewer GHGs is, for instance, not a new policy concern. In various countries, limits on emissions from automobiles have been around since the 1970s. Still, older equipment and automobiles (e.g., 'vintage' ones) as well as heavily polluting industries (i.e., oil, gas, and cement, etc.), are not clearly impacted by these policies. Vintage equipment is usually not restricted as much as newer equipment by climate policy. Thus, these sectoral and technological considerations also need to be carefully integrated and applied for creating climate policy indicators.

Policy Flexibility, Innovation, and Technology

Beyond the sectoral, temporal, and qualitative differences germane to the impacts of climate policies, there are also specific 'points of incidence' that the

27. David Coen, Julia Kreienkamp, and Tom Pegram, *Global Climate Governance* (Cambridge: Cambridge University Press, 2020). https://doi.org/10.1017/9781108973250

28. Brunel and Levinson, 'Measuring the stringency.'

29. W. Pieter Pauw, et al., 'Beyond headline mitigation numbers: we need more transparent and comparable NDCs to achieve the Paris Agreement on climate change,' *Climatic Change* 147 (March 2018): 23–29. https://doi.org/10.1007/s10584-017-2122-x researcher should reckon. Points of incidence refer to where policy targets harm to the climate, identifying new technologies and innovations needed. Once identified, the point of incidence draws in innovators.[30] The aim is to encourage environmental-economic win-wins through innovation and industrial upgrading, which is one crux of green growth.[31]

Examples of climate policies that locate the point of incidence are, among others, performance standards, environmental taxes, or tradable air pollution permits. They are commonly used to encourage renewable energy innovation and deployment.[32] Hence, the state has a vital role to play to induce new climate technology innovations as well as disruptive clean energy transitions.[33] Well-crafted climate regulations can, moreover, signal inefficiencies, reduce uncertainty, and pressure firms to innovate. This has the effect of 'levelling the playing field' and reducing the costs of innovation-based learning.[34] Climate policy can, therefore, become a 'tool for competitive advantage […] for minimising ecological impacts of economic production while enhancing the competitiveness of firms.'[35]

Policy Stability versus Uncertainty

In terms of green growth, policy stability is critical. Much-needed climate technologies are inherently difficult and expensive to produce, which is the main reason that policy stability is so important. Unstable policies, however,

30. Adam B. Jaffe, Richard G. Newell, and Robert N. Stavins, 'Environmental Policy and Technological Change,' *Environmental and Resource Economics* 22, no 1 (February 2002): 41–70. https://doi.org/10.1023/A:1015519401088

31. Christian Binz, et al., 'Toward technology-sensitive catching-up policies: insights from renewable energy in China,' *World Development* 96 (August 2017): 418–37. https://doi.org/10.1016/j.worlddev.2017.03.027

32. Friedmann Polzin, et al., 'Public policy influence on renewable energy investments-A panel data study across OECD countries,' *Energy Policy* 80 (May 2015): 98–111. https://doi.org/10.1016/j.enpol.2015.01.026

33. Florian Egli, Nick Johnstone, and Carlo Menon, *Identifying and inducing breakthrough inventions: An application related to climate change mitigation* (Paris: OECD Publishing. 2015). https://dx.doi.org/10.1787/5js03zd40n37-en; Phil Johnstone and Peter Newell, 'Sustainability transitions and the state,' *Environmental Innovation and Societal Transitions* 27 (June 2018): 72–82. https://doi.org/10.1016/j.eist.2017.10.006; Phil Johnstone, et al., 'Waves of disruption in clean energy transitions: Sociotechnical dimensions of system disruption in Germany and the United Kingdom,' *Energy Research & Social Science* 59 (January 2020): 101287. https://doi.org/10.1016/j.erss.2019.101287

34. Michael E. Porter and Claas van der Linde, 'Toward a New Conception of the Environment-Competitiveness Relationship,' *Journal of Economic Perspectives* 9, no. 4 (Fall 1995): 97–118. https://doi.org/10.1257/jep.9.4.97

35. Paul Shrivastava, 'Environmental technologies and competitive advantage,' *Strategic Management Journal* 16, no. 1 (1995): 183–200. https://doi.org/10.1002/smj.4250160923 effectively serve as a brake on innovation.[36] For example, the US, Canada, and Australia have had unstable climate change policies introducing at first stringent climate policy regulations repealed by successive governments, which has had some serious consequences for green innovation such as reversing the benefits of green growth.[37] On the other hand, evidence suggests that flexible and well-timed climate policy produces economic and climate win-wins.[38]

Popular Climate Policy Indicators

Overall, reliable climate policy indicators should be able to 'simplify, quantify, analyze and communicate the complex and complicated information (sic)'[39] underlying policy decisions and their constituent effects on the ground. As such, climate policy and governance indicators assess stringency, timing, efficacy, location, and other effects on the economy and the environment. In this light, several efforts have been made to approximate the impact of climate change policies at global and national levels.

Bättig, Brander, and Imboden make an important contribution in this respect. In their Climate Change Index, they aim to inform policymakers of the environmental changes that relate to policy for future scenarios.[40] While many efforts have been made to model future climate and economic impacts of climate policy through 'integrated assessment models,'[41] the advantage of Bättig,

36. Ivan Haščič, et al., 'Effects of environmental policy on the type of innovation,' *OECD Journal: Economic Studies 2009*, no. 1 (March 2009): 1–18. https://doi.org/10.1787/eco_studies-v2009-art2-en

37. Dani Rodrik, 'Green industrial policy,' *Oxford Review of Economic Policy* 30, no. 3 (Autumn 2014): 469–91. http://www.jstor.org/stable/43664659; Sam Fankhauser, et al., 'Who will win the green race? In search of environmental competitiveness and innovation,' *Global Environmental Change* 23, no. 5 (October 2013): 902–13. https://doi.org/10.1016/j.gloenvcha.2013.05.007

38. Daniel C. Esty and Andrew Winston, *Green to Gold: How Smart Companies Use Environmental Strategy to Innovate, Create Value, and Build Competitive Advantage*, rev. ed. (New Jersey: John Wiley & Sons, 2009); Angshuman Sarkar, 'Promoting Eco-Innovations To Leverage Sustainable Development Of Eco-Industry And Green Growth,' *European Journal of Sustainable Development* 2, no. 1 (February 2013): 171–224. https://doi.org/10.14207/ejsd.2013.v2n1p171; Stefan Ambec, 'Gaining competitive advantage.'

39. Singh, et al., 'An overview of sustainability,' 282.

40. Michèle B. Bättig, Simone Brander, and Dieter M. Imboden, 'Measuring countries' cooperation within the international climate change regime,' *Environmental Science & Policy* 11, no. 6 (October 2008): 478–89. https://doi.org/10.1016/j.envsci.2008.04.003

41. Ajay Gambhir, 'Planning a Low-Carbon Energy Transition: What Can and Can't the Models Tell Us?' *Joule* 3, no. 8 (August 2019): 1795–98. http://dx.doi.org/10.1016/j.joule.2019.07.016; Volker Krey, et al., 'Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models,' *Energy* 172 (April 2019): 1254–67. https://doi.org/10.1016/j.

Brander, and Imboden's approach is it posits a single index that aims at simplification and streamlining, which yields climate policy indicators much more useful for policy-makers.

By the same token, Li, Du, and Wei construct a national environmental policy stringency indicator based on environmental treaties. They find significant differences in climate policy indicators across countries. This is because, even though emissions mitigation has global goods benefits, it has varying costs depending on the country or region and the type of energy countries are switching away from.[42] In the same vein, Schmidt and Fleig conducted a comprehensive assessment of climate laws in 171 countries across 27 years. They show how climate policy stringency has increased significantly, especially with respect to energy supply and demand, but not as much for the transport sectors.[43] Likewise, their study indicates that variation across countries vis-a-vis climate policy depends on EU membership, the environmental vulnerability of a country, and, not surprisingly, income level.[44]

Climate policy simulation could also be an immensely important tool to develop and roll out green growth policies carefully. Simulations model a policy beforehand to understand its potential impacts. Before introducing a policy, for example, simulations could be run to determine how it might impact the economy, its firms, and innovators. In this regard, two questions are raised: 1) Will the potential policy induce firms to create innovative new environmental technologies? 2) Will it lead to end-of-pipe environmental technology solutions?[45] Sterman et al. experiment with this idea, simulating negotiations under the potential outcomes of the United Nations Framework Convention on

energy.2018.12.131; Damjan Krajnc and Peter Glavič, 'A model for integrated assessment of sustainable development,' *Resources, Conservation and Recycling* 43, no. 2 (January 2005): 189–208. https://doi.org/10.1016/j.resconrec.2004.06.002

42. Aijun Li, Nan Du, and Qian Wei, 'The cross-country implications of alternative climate policies,' *Energy Policy* 72 (September 2014): 155–63. https://doi.org/10.1016/j.enpol.2014.05.005

43. Schmidt and Fleig, 'Global patterns.'

44. Ibid.

45. Henrik Hammar and Åsa Löfgren, 'Explaining adoption of end of pipe solutions and clean technologies-Determinants of firms' investments for reducing emissions to air in four sectors in Sweden,' *Energy Policy* 38, no. 7 (July 2010): 3644–51. https://doi.org/10.1016/j.enpol.2010.02.041

Climate Change (UNFCCC) negotiations.[46] Similarly, Doukas and Nikas pose an 'expert decision support system' that breaks down linguistic elements in climate negotiations and seeks to draw together the disparate strands of literature on decision-making for climate policy.[47] Yet, though promising, this body of literature remains underdeveloped.

While the approaches above allow measuring environmental 'outputs,' Bernauer and Böhmelt take a slightly different approach. They rank countries according to their participation in the Kyoto Protocol (e.g., climate policy inputs).[48] The purpose of this ranking is to assess the stringency of country-level climate policy. Using the Climate Change Cooperation Index (C3-I), they attempt to measure political behavior and greenhouse gas emissions (outputs and outcomes),[49] this indicator making an important contribution to the literature.[50] Lastly, researchers from German-Watch have created the popular Climate Change Performance Index (CCPI).[51] The CCPI provides a time-series indicator covering 57 countries and the European Union. It divides its index into GHGs, renewable energy, energy usage, and climate policy.

In this section, we reviewed how spatial, temporal, geographical, and qualitative differences can lead to widely differentiated effects of climate policies on the ground. Likewise, we discussed some relevant climate policy indices other researchers have already developed. In the following section, we explore several examples of climate policy transformation. Additionally, we address some techniques that can be applied to enhance climate policy indicators. Lastly, we

46. John Sterman, et al., 'World climate: A role-play simulation of climate negotiations,' *Simulation & Gaming* 46, no. 3-4 (June 2015): 348-82. https://doi.org/10.1177%2F1046878113514935

47. Haris Doukas and Alexandros Nikas. 'Decision support models in climate policy,' *European Journal of Operational Research* 280, no. 1 (January 2020): 1–24. https://doi.org/10.1016/j.ejor.2019.01.017

48. Thomas Bernauer and Tobias Böhmelt, 'National climate policies in international comparison: The Climate Change Cooperation Index,' *Environmental Science & Policy* 25 (January 2013): 196–206. https://doi.org/10.1016/j.envsci.2012.09.007

49. Ibid.

50. Erick Lachapelle and Matthew Paterson, 'Drivers of national climate policy,' *Climate Policy* 13, no. 5 (September 2013): 547–71. https://doi.org/10.1080/14693062.2013.811333

51. Jan Burck, Franziska, Marten, and Christoph Bals, *The Climate Change Performance Index: Background and Methodology 2016* (Bonn: GermanWatch, 2016); Bernauer and Böhmelt, 'National climate policies;' Jan Burck, Christoph Bals, and Simone Ackermann, *The Climate Change Performance Index: Background and Methodology 2009* (Bonn: GermanWatch, 2009).

describe the development and transformation of our own three indices (i.e., the green growth investment potential indicator, the revised UNFCCC cooperation indicator, and the climate policy stability indicator).

6.3. Climate Policy Indicator Transformation

In the previous section, we addressed important considerations researchers should account for when building and transforming climate policy indicators. In this section, we discuss several important contributions to climate policy indicator transformation and posit a transformation and development of a composite climate and green growth index. In the final section of this chapter, we discuss some implications and further methods that can be deployed.

Dimensionality Reduction

Climate governance involves multiple socio-economic, political, and policy decisions.[52] It is a complex process predicated on a number of policy inputs and outputs. Thus, the issue of high dimensionality in climate policy indicators often arises. These problems are referred to as 'endogeneity' and 'auto-correlation' in quantitative empirical models.[53] Elsewhere, these issues have similarly been raised and recognised as problematic for some time.[54] To mitigate these concerns, researchers can reduce the dimensions of the input variables with the effect of providing more robust output indicators.[55] After a climate policy index is created, for instance, such dimension-reduction techniques can be performed. In this vein, transformations involve re-scaling, normalisation, different weighting, and aggregation techniques. Hence, indicator transformation re-calibrates an indicator to fit a specific policy or research question.

52. Bruno Turnheim, Paula Kivimaa, and Frans Berkhout, eds., *Innovating climate governance: moving beyond experiments* (Cambridge University Press, 2018).

53. Cohen and Tubb, 'Impact of Environmental Regulation.'

54. David F. Andrews, 'Plots of high-dimensional data,' *Biometrics* 28, no. 1 (March 1972): 125–36. http://dx.doi.org/10.2307/2528964

55. Angel Hsu and Alisa Zomer, 'Environmental performance index,' Wiley StatsRef: Statistics Reference Online, last modified November 13, 2016. https://doi.org/10.1002/9781118445112.stat03789.pub2

Another method to deal with multi-dimensionality or auto-correlation during indicator transformation is building a composite indicator.[56] This method incorporates a discrete weighting system over a set of variables.[57] Composite indicators have been used to mitigate the multidimensionality issues raised above.[58] Importantly, nonetheless, even with composite indicators, several research decisions are required and if they are not carefully implemented, these can lead to biases. In short, a reduction of dimensions allows for more meaningful empirical analysis to be done. It is particularly useful for cross-country or cross-industry analysis, which indeed are a main goal of the NDCs under the Paris Climate Agreement.[59] Other tools for indicator transformation, apart from creating composite indicators, are discussed below.

Transformation and Application

Our argument throughout this chapter is that automated approaches can reduce much of the inherent biases in climate policy indicators cited as a recurrent underlying issue that has permeated the scholarship.[60] To reduce potential biases, researchers have successfully deployed tools to enhance existing climate policy indicators. Dimension reduction techniques, which take high dimensional data and reduce these data to smaller dimensions, can be employed through factor analysis and polychoric correlation or by means of principal component analysis (PCA) based on Spearman correlations. Also, pre-cleaning methods such as using Cronbach's alpha to determine the reliability of input values might be utilised.[61] Below we discuss some of these transformations, and at the end of this section, we present our sample transformation.

56. Frederik Booysen, 'An Overview and Evaluation of Composite Indices of Development,' *Social Indicators Research* 59 (August 2002): 115–51. https://doi.org/10.1023/A:1016275505152; Nardo, et al., *Tools for Composite Indicators*.

57. Booysen, 'An Overview and Evaluation.'

58. Ibid.; Nardo, et al., *Tools for Composite Indicators*; Brunel and Levinson, 'Measuring the stringency.'

59. Pauw, et al., 'Beyond headline mitigation numbers.'

60. Cohen and Tubb, 'Impact of Environmental Regulation.'

61. Galeotti, et al., 'Environmental policy performance;' Francesco Nicolli and Francesco Vona, 'The evolution of renewable energy policy in OECD countries: aggregate indicators and determinants,' In *Political Economy and Instruments of Environmental Politics*, eds. Friedrich Schneider, Andrea Kollmann, and Johannes Reichl, (Cambridge: The MIT Press, 2015), 117–48.

Decomposition: Principal Component Analysis and Climate Policies

To effectively address the different typologies of climate policies that can co-exist within an economy and to estimate how such policy differences impart widely differing effects, Kalamova and Johnstone cluster climate policies by the 'points of incidence' and targeted policy dimensions. They break down the climate policy indicator by price-based, voluntary, and quantity-based policies.[62] In this manner, they reduce some selection bias while also reducing underpinning correlations in the data.[63] After clustering the climate policies according to their specific point of incidence, they reduce correlations and dimensions by applying PCA.

In general, PCA involves identifying the directions of variables referred to as principal components (PCs) or orthogonal sub-indices. These explain most of the variance in the data. Concerning indicators, PCs make up linear combinations of the broader policy variables and are particularly well suited to deal with variation in the index data. This has the effect of removing extraneous or over-correlated data. In technical parlance, this is done by developing a covariance matrix of the data and performing eigen-decomposition on the covariance matrix. The eigenvectors are then sorted from largest to smallest corresponding eigenvectors to 'transform a given set of variables into a composite set of components that are orthogonal to, i.e., totally uncorrelated with, each other [and requires] no particular assumptions.'[64] However, skewness and kurtosis can violate the normality assumption; if this occurs, PCA can bias the results. To counteract this, a maximum likelihood estimator is used to fit the data to a continuous normal distribution before calculating the correlation matrix. In this line, beyond Johnstone et al., others have applied PCA to the OECD's Environmental Policy Index. We briefly discuss this below.

62. Margarita Kalamova and Nick Johnstone, 'Environmental Policy Stringency and Foreign Direct Investment,' in *A Handbook of Globalisation and Environmental Policy, Second Edition*, eds. Frank Wijen et al. (Northampton: Edward Elgar Publishing, 2012), 34–56.

63. Ibid.

64. Bernard J. Morzuch, 'Principal components and the problem of multicollinearity,' *Journal of the Northeastern Agricultural Economics Council* 9, no. 1 (April 1980): 81–83. http://bitly.ws/rIDT

Transformation: The OECD's Environmental Policy Index (EPS)

PCA has also been applied to uncover latent variables that contribute to climate policy indicators. It has likewise helped to explain the underpinning distribution in multivariate data in the OECD's Environmental Policy Stringency Index (EPS), initially developed by researchers at the OECD.[65] The OECD's EPS is widely used as a climate policy stringency proxy.[66] The indicator is divided into non-market-based (NMB) and market-based (MB) instruments. NMB policies include emissions standards limits (e.g., SOX, NOX, particulate matters, and sulfur content of diesel) and government energy-related R&D expenditures as a percentage of GDP. Market-based policies include feed-in tariffs (e.g., solar and wind energy), taxes (e.g., on CO2, SOX, NOX, and diesel), certificates (e.g., white, green, and CO2), and the presence of deposit and refund schemes (DRS). All EPS variables are continuous except DRS because they are dichotomous. EPS covers 33 countries (OECD countries and the 'BRICS,' i.e., Brazil, Russia, India, China, and South Africa). Diverse variables contribute to this indicator such as dealing with greenhouse gas emissions, renewable energy, and other noxious atmospheric substances. For this reason, the EPS could more appropriately be defined as a climate rather than an environmental policy indicator.

While the EPS has been an important indicator in empirical climate policy research, some underlying problems arise with correlation and dimensionality. One main impediment is that it is composed of both continuous and discrete input variables. To address some of the issues of correlation and dimensionality, it can be transformed before empirical and modelling usage. Accordingly,

65. Enrico Botta and Tomasz Koźluk *Measuring environmental policy stringency in OECD countries: A composite index approach (Working Paper)* (Paris: OECD Publishing, 2014). https://doi.org/10.1787/5jxrjnc45gvg-en; Nicolli and Vona. 'Evolution of renewable energy policy.'

66. Nicolli and Vona. 'Evolution of renewable energy policy;' Tomasz Kozluk and Vera Zipperer, 'Environmental policies and productivity growth,' *OECD Journal: Economic Studies* 2014, no. 1 (March 2015): 155–85. https://doi.org/10.1787/eco_studies-2014-5jz2drqml75j; Popp, *Environmental policy and innovation*; Kyle Stuart Herman and Jun Xiang, 'Environmental regulatory spillovers, institutions, and clean technology innovation: A panel of 32 countries over 16 years,' *Energy Research & Social Science* 62 (April 2020): 101363. https://doi.org/10.1016/j.erss.2019.101363; Kyle Stuart Herman and Jun Xiang, 'Induced innovation in clean energy technologies from foreign environmental policy stringency?' *Technological Forecasting and Social Change* 147 (October 2019): 198–207. https://doi.org/10.1016/j.techfore.2019.07.006

researchers have taken the EPS' 15 variables and compressed these with PCA to compute a more robust and less correlated overall indicator. For instance, Nicolli and Vona extract principal components (PCs) and subsequently, create three sub-indices) for renewable energy generation, renewable energy certificates (RECs), and R&D credits.[67] In a similar vein, Galeotti et al. sum the different simulated indicators they create with the OECD's EPS to effectively capture the 'diversification of the environmental policy portfolio.'[68] Thereafter, they use PCA to reconstruct 'emissions-based' indicators, which helps reduce the correlated variables to smaller latent PCs.[69]

Even though the aforementioned transformations represent important contributions to the literature, there remains much space to further develop this body of research and analysis. As a main consequence of this lack of development, substantial disparities remain throughout the empirical literature.[70] Thus, we argue that researchers should focus efforts on transforming existing indicators such as the OECD's EPS through machine-learning, deep-learning, and pattern discovery. This will increase the veracity of these indicators and provide better support to empirical models. Furthermore, these methods can also help to provide real-time policy feedback, which is a subject we tackle in the final section of this chapter.

Policy Feedback

Automated Policy feedback is a fervent and burgeoning field since this emerging research area could have significant impacts on climate policy, green growth, and governance for the environment. A related concept is 'anticipatory governance' that enables policymakers to quickly tweak policies based on rapid feedback.[71] These feedbacks can also link between domains: firms and government, economy and the environment, and investors and entrepreneurs, who are all critical to the success of an environmental policy with respect to the economy.

67. Nicolli and Vona. 'Evolution of renewable energy policy.'

68. Galeotti, et al., 'Environmental policy performance.'

69. Ibid.

70. Brunel and Levinson, 'Measuring the stringency;' Galeotti, et al., 'Environmental policy performance.'

71. Stefano Maffei, Francesco Leoni, and Beatrice Villari, 'Data-driven anticipatory governance. Emerging scenarios in data for policy practices,' *Policy Design and Practice* 3, no. 2 (May 2020): 123–34. https://doi.org/10.1080/25741292.2020.1763896

Emerging methods are very promising along these lines. For example, Kong, Feng, and Yang demonstrate how governments can be provided with real-time policy and monitoring feedback for environmental regulations.[72] Such tools have likewise been deployed to report on energy security and energy sustainability.[73] As a corollary, simulation could allow careful calibration at the local level that often suffers from the simultaneity problem because federal environmental policies impact smaller jurisdictions in multifarious ways. The scenarios can be repeated hundreds of times and provide predictions of different policy interventions.[74] In this manner, policymakers might compare the different results and 'collaboratively distinguish the best solutions for tackling the situation under investigation.'[75] Open-source tools such as Rapidminer, KNIME, and WEKA can provide solutions here. Additionally, although some simulations have indeed been carried out for climate change policies such as the integrated assessment models, these have not fully materialised through machine-aided techniques yet. Hence, there is much room for future research in this area.

The Climate Policy Competitiveness Index

As mentioned above, green growth, innovation, and climate policy form a confluence of important subject areas that can be adequately addressed with climate policy indicators. However, high-dimensionality, auto-correlation, or lack of variation within such indicators have impeded their more effective development and usage. In this subsection, to demonstrate the application of indicator construction and transformation, we build three composite indexes. The 'off-the-shelf' indicators we use to build our composite indicator are the following:

72. Yuan Kong, Chao Feng, and Jun Yang, 'How does China manage its energy market? A perspective of policy evolution,' *Energy Policy* 147 (December 2020): 111898. https://doi.org/10.1016/j.enpol.2020.111898

73. Ibid.; Kapil Narula and B. Sudhakara Reddy, 'Three blind men and an elephant: The case of energy indices to measure energy security and energy sustainability,' *Energy* 80 (February 2015): 148–58. https://doi.org/10.1016/j.energy.2014.11.055

74. Aggeliki Androutsopoulou and Yannis Charalabidis, 'A framework for evidence based policy making combining big data, dynamic modelling and machine intelligence,' in *Proceedings of the 11th International Conference on Theory and Practice of Electronic Governance,* Galway, 2018 (Galway: Association for Computing Machinery), 575–83.

75. Ibid., 580.

- The climate change performance index (CCPI).[76]
- The World Economic Forum's competitiveness index (WEF).[77]
- The World Bank's ease of doing business index (EDB).[78]
- The UNFCCC cooperation index.[79]

We develop three separate composite indicators using the above: (1) a green growth investment potential indicator (GGPI) with the CCPI, EDB, and WEF; (2) a revised cooperation index (CI) with the UNFCCC CI's six variables; and (3) a climate stability indicator (CSI). These combine the variables that are included in the four indexes above, averaging the standardised component variables. To visualise the results in PCA space, we derive the first two principal components of each data matrix. FIGURES 6, 7, and 8 illustrate the first principal components representing the maximum variance directions of data. These components account for the variance dispersed through the various indices.

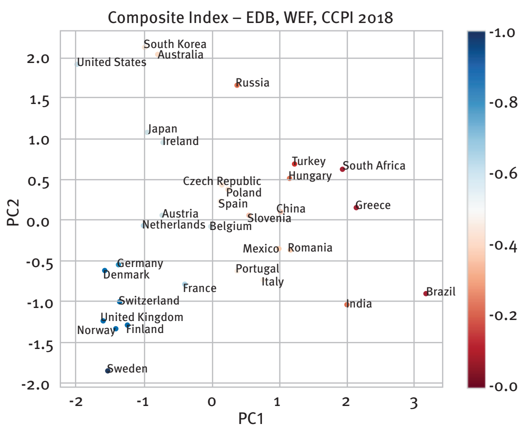

FIGURE 6. Green Growth Investment Potential (GGIP) Indicator

Source: Prepared by authors.

76. Burck, Marten, and Bals, *Climate Change Performance Index.*

77. Klaus Schwab, ed, *The Global Competitiveness Report 2019* (Cologny: World Economic Forum, 2019).

78. 'Ease of Doing Business Score and Ease of Doing Business Ranking,' World Bank, accessed May 24, 2022. http://bitly.ws/rIxt

79. Bättig, Brander, and Imboden, 'Measuring countries' cooperation,' The GGIP composite indicator (WEF, EDB, CCPI) shows that Sweden, the U.K, Norway, Finland, and Denmark are the best climate investment countries in 2018. The worst countries for climate investment based on this indicator are Iran, Algeria, Saudi Arabia, Argentina, and Egypt.

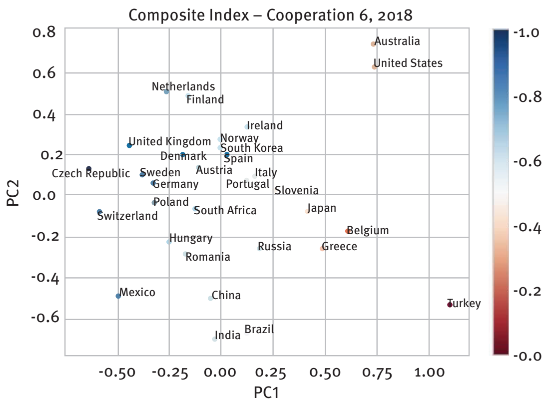

FIGURE 7. Revised UNFCCC Cooperation Indicator.

Source: Prepared by authors.

The revised UNFCCC-CI demonstrates that the Czech Republic, Switzerland, and Mexico are the most cooperative countries regarding climate change policy. The least cooperative, based on our composite indicator, are the United States, Belgium, and Turkey for 2018.

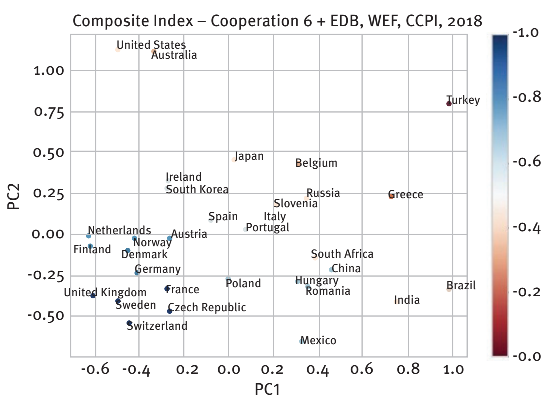

FIGURE 8. Climate Policy Stability Indicator

Source: Prepared by authors.

The Climate Policy Stability Indicator combines all of those listed above and demonstrates where the most stable climate investments can be made, at the country level. Sweden and the U.K. have the most stable environments for climate change policy, whilst also cooperating highly with the UNFCCC process. BRICS countries fall to the bottom of this indicator, which does not bode well for meeting the global objectives of the Paris Agreement.

Let us summarise the composite indicators we have created and briefly discussed. Our main purpose is not to introduce a new index, but to deploy some of the methods and tools discussed in this paper to transform these 'off-the-shelf' indicators above. Our three indicators, in short, provide a snapshot of green growth competitiveness at the country level. They suggest what the most competitive countries vis-a-vis climate change policies are and who is winning the 'green race.'[80] The indicators are not constructed for empirical application but rather to provide an example of how the considerations discussed throughout this paper, coupled with some transformation methods, may be effectively employed by future researchers. We expect that future research will greatly expand upon these methods.

6.4. Discussion

In the previous section, we discussed the transformation of climate policy indicators and presented our examples. We created three separate indicators for some countries in 2018. While this serves as an example, this line of research could be developed much further in the future. In this section, we address other important tools which might equip future researchers to undertake these important tasks. In this train of thought, we highlight many of the existing tools to help researchers construct, transform, and apply climate policy indicators.

Tools and Methods for Future Research and Analysis

There are a number of automated data collection techniques that can help enhance climate policy indicators and enable researchers in both developing

80. Fankhauser, et al., 'Who will win?'

and developed countries to create and transform climate policy indicators. These are often free to use (e.g., open-source) and include, but are not limited to Scrappy, Apify SDK, Cheerio, PySpider, UiPath, Rapidminer, KNIME and WEKA, TraMineR, Grafter, and OpenRefine.

t-distributed Stochastic Neighbor Embedding (t-SNE)

Graphical display of high-dimensional data has become important to pattern discovery and machine learning. A main method along these lines called t-distributed stochastic neighbor embedding, i.e., 't-SNE,' allows for the transformation of data that has many input variables. It has proven to be highly effective in producing a graphical display of high-dimensional data.[81] Like PCA, which is discussed and applied above, t-SNE effectively reduces high-dimensional data. However, in contrast to PCA, t-SNE preserves rather than maximises variance. To maximise the variance in the underlying data, especially after visualisation, it is helpful to show what would otherwise be difficult when detecting differences in climate policy across countries and over time (e.g., with PCA). In this sense, preserving the variance, as in t-SNE, is more reliable for further empirical analysis because it represents the underlying data more exactly.

Support Vector Machines (SVMs) and Neural Networks

Another deep-learning tool is support vector machines (SVMs). It could help classify and, in turn, re-classify the hundreds of climate policies found around the world. In this vein, SVMs excel in regressing data in high dimensions. This would enable quicker identification of troublesome and inconsistent climate policies that show limited benefits or are otherwise incapable of instantiating substantive changes on the ground.

Yet, while SVMs are considered easier to implement and are also able to model data that are not linearly separable, neural nets are typically harder to configure and debug due to the high number of hyperparameters required for fine-tuning. Similar to SVMs, neural networks, which are 'opaque function approximators' that perform successive computations on signals through a

81. Laurens van der Maaten and Geoffrey Hinton, 'Visualizing data using t-SNE,' *Journal of Machine Learning Research* 9, no. 11 (November 2008): 2579–2605. http://bitly.ws/rIxK biologically inspired architecture of layers and nodes, can also be important tools here. Elsewhere, Gründler and Krieger have leveraged SVM to create a democracy index covering over 50 years and over a hundred countries.[82] This might be extended to create a similar index for climate policy stringency across countries and over time.

One of the many recent applications of neural networks is in natural language processing (NLP) where patterns in textual data such as Twitter streams can be used to infer public sentiment.[83] Another benefit, in contrast to SVMs, is that neural nets can be updated online, which could enable real-time inferences. Such tools might be particularly critical for 'anticipatory' climate governance; in other words, to enable swifter identification and analysis of climate policies concerning the economy. Such semi-automated techniques could also be quite useful to refine and re-calibrate climate proxies as countries alter their policy strategies because of political changes. Or they could be used to gauge public sentiment on emerging climate policies.

6.5. Conclusion

In this chapter, we explored the issue of climate policy indicators, their inherent complexity, design, transformation, and empirical application. While a number of climate policy indicators exist, there remain many underlying problems with these. In addition, as green growth includes not only climate and environmental policy but also green competitiveness and industrial policy concerns,[84] transformation and construction of composite indicators, as we have shown, is incredibly important. These problems can enable rapid and accurate assessment of policy, and climate policy impacts on the environment and the

82. Klaus Gründler and Tommy Krieger, 'Democracy and growth: Evidence from a machine learning indicator,' *European Journal of Political Economy* 45 (December 2016): 85–107. https://doi.org/10.1016/j.ejpoleco.2016.05.005

83. Ana Reyes-Menendez, José Ramón Saura, and Cesar Alvarez-Alonso, 'Understanding# WorldEnvironmentDay user opinions in Twitter: A topic-based sentiment analysis approach,' *International Journal of Environmental Research and Public Health* 15, no. 11 (November 2018): 2537. https://doi.org/10.3390/ijerph15112537

84. René Kemp and Babette Never, 'Green transition, industrial policy, and economic development,' *Oxford Review of Economic Policy* 33, no. 1 (January 2017): 66–84. https://doi.org/10.1093/oxrep/grw037 economy. Plus, as a main consequence of the relative lack of development in climate policy indicators, policymakers are unable to readily assess the impacts of climate policy on the economy, which is a salient issue, especially in the era of widespread green growth policies. We have proposed to follow recent success using PCA to transform existing indicators. Going one step further, we have suggested deploying new machine learning, pattern discovery, and deep learning techniques. We then introduced our indicators, which constitutes only a starting point for future research.

The techniques discussed in this chapter are no panacea. Great caution is warranted when employing these methods. While human biases are likely to be reduced, they will remain. This is why we provided a detailed discussion on the topical issues impacting climate policy transformation. Even though much hope is pinned on machine learning, pattern discovery, and deep learning, ultimately researchers have to make important, well-reasoned, appropriate, and logical research decisions. If done correctly, however, the impact of these indicators can be significant, especially considering the massive funding now devoted to green growth. Beyond the responsibility for accurate and robust research, therefore, researchers must also be cognizant that climate policy indicators will, on their own, have highly meaningful impacts on the future of the global environment.

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